Space-Air-Ground IoT Network and Related Key Technologies

Tao Hong, Weiting Zhao, Rongke Liu, and Michel Kadoch

Abstract

The integration of multidimensional networks such as space, air and ground is the future trend of the IoT. In this article, we introduce the SAG IoT network paradigm, including its composition and network architecture. Network slicing, the core 5G technology, will be applied to the SAG IoT network. The wide use of mmWave and UAVs is to produce many new scenarios, and it is necessary to study the effects of UAVs on mmWave channels in these new scenarios. In addition, mmWave imaging technology can provide a basis for this research. Machine learning is an important new technology that can be widely used in the SAG IoT. Simulation and measurement are both important means of evaluating the performance of communication systems. To cope with the emerging new applications and technologies, a cloud-based modular simulation system is introduced for 5G and future IoTs; this system is characterized by high efficiency, flexible configuration and high precision.

Introduction

In recent years, with the maturity of related technologies, more and more new IoT applications have emerged. At the same time, unmanned aerial vehicles (UAVs) have been widely used in many fields. Combining UAVs with new communications technologies such as 5G new radio (NR) and new IoT applications could provide more innovative services [1]. When UAVs are equipped with communications or IoT devices, a UAV IoT network is to be formed. This IoT network could provide services such as data collection, target identification and temporary communication, and it has the advantages of flexible deployment, a wide application range and low cost.

The satellite network covers a wide area and can provide seamless connectivity to ocean and mountain areas, air networks can enhance capacity in areas with high service demand, and densely deployed ground segment systems can support high data rate access. The integration of these networks has attracted interest from academics and industry experts, and several commercial integrated systems have emerged in recent decades, such as the Iridium system. Many papers have been written on issues such as spectrum allocation and traffic offloading, and so on. However, these research works typically target only specific single services, such as voice and video, and have not integrated IoT services into the systems [2]. Therefore, in this work, we propose a novel SAG IoT network paradigm. The SAG IoT is an IoT network that integrates satellite, air and ground networks. It is the product of the deep integration of satellite communication, air communication, 5G communication and IoT technologies. In the future, it will become the main form of comprehensive service, providing wide coverage and high-speed communication services. Each node in the space, air and ground planes must closely cooperate and coordinate with every other node in order to transmit messages efficiently, and to best meet the needs of the many fields in which SAG IoTs are employed, including aviation, fisheries, environmental monitoring and other fields.

The "smart city" is one of the prominent applications of the IoT and offers diverse innovative services to citizens. In the era of SAG, the concept of the smart city is about to become a reality. With the emergence of new applications, mobile data traffic will grow explosively. Moreover, SAG IoTs are expected to support vertical markets with different requirements, including such diverse areas as the automotive industry, environmental protection agencies, and medical search and rescue. These verticals have different requirements and will require SAG IoTs to be flexible, manageable, scalable, customizable and able to support multi-service demands. Network slicing (NS) is considered an effective means to achieve the above goals. It can divide the underlying public physical network into multiple end-to-end (E2E) logical sub-network. Each of these logical sub-networks is created on demand and isolated from others, so as to best provide services for specific users. With the help of NS, the network resources of multi-domain infrastructures can be efficiently allocated to multiple network slices according to the real-time needs of the users [3].

mmWave is the main frequency band of 5G and future IoTs. It enables the use of more spectra to achieve a larger data rate. In addition, new service requirements will create new application scenarios. Understanding the channel characteristics of the new frequency bands and new scenarios will be critical to the development of new applications for the SAG IoT [4]. Thus, it is necessary to model the channel for these new frequency bands and new application scenarios, as the new channel model will be an important reference for network planning and performance analysis. The traditional two-dimensional (2D) modeling method considers only

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the propagation of the signal in the azimuthal plane, which may lead to inaccurate estimation of channel capacity and spatial correlation [5]. The SAG IoT is a stereo network, and multipath propagation is an important characteristic of the mmWave signal. Therefore, for new channel modeling, a three-dimensional (3D) modeling method that considers channel propagation in space should be used.

As an important part of the SAG IoT, the UAV IoT will be widely used. However, the UAV itself is scattered, and flying UAVs will have a non-negligible impact on the propagation of wireless signals. This effect can be divided into two aspects:

- The reflection, scattering and diffraction effects of the UAV will change the propagation direction of the signal and produce multipath effects.
- The motion of the UAV will cause frequency shifts in the signal.

However, there is currently no literature that addresses the effects of UAVs on signal propagation from a mathematical perspective. Thus, an analysis of 3D mmWave channel modeling under various UAV scenarios is needed. To model the mmWave channel under different UAV scenarios, the first step is to study the reflection, scattering and diffraction effects of the UAV on the signal by performing 3D imaging of the UAV under mmWaves. This method will obtain the characteristics of the UAV under the corresponding aspects.

Network simulation refers to the use of software to simulate the behavior of a specific network. Such simulation can quickly obtain the performance parameters of the network at a very low cost. At present, this type of simulation is widely used in network design, optimization and technical verification [6]. However, the new network architecture, new application scenarios and new key technologies that have emerged with the SAG IoT have brought new challenges to the traditional simulation platforms. To this end, we introduce a new simulation system for 5G and SAG IoT. Some measurement work is also needed to provide the necessary parameters for the new simulation system.

The main contributions of this work are summarized as follows:

- A novel SAG IoT network paradigm based on the Space-Air-Ground heterogeneous architecture is proposed, and the network architecture and key technologies of this novel SAG IoT are introduced in detail.
- The RF impact of UAVs on communication in future IoT systems is proposed, multipath and frequency shift factors are included. Then mmWave 3D imaging is used to study the scattering characteristics of UAVs on mmWave; the signal frequency shift caused by the micro-Doppler effect of UAVs is also analyzed.
- A modular simulation system based on cloud computing is proposed for future SAG IoT applications, and the simulation results prove the content discussed in this article.

The rest of this article is organized as follows. In the following section, we introduce the basics of SAG IoT, including its network architecture and components. Then, we discuss the key technologies supporting this amazing paradigm, such as network slicing and mmWave channel modelling. Following that, the new measurement and simulation results are presented to justify the performance of our design. Finally, we conclude the article.

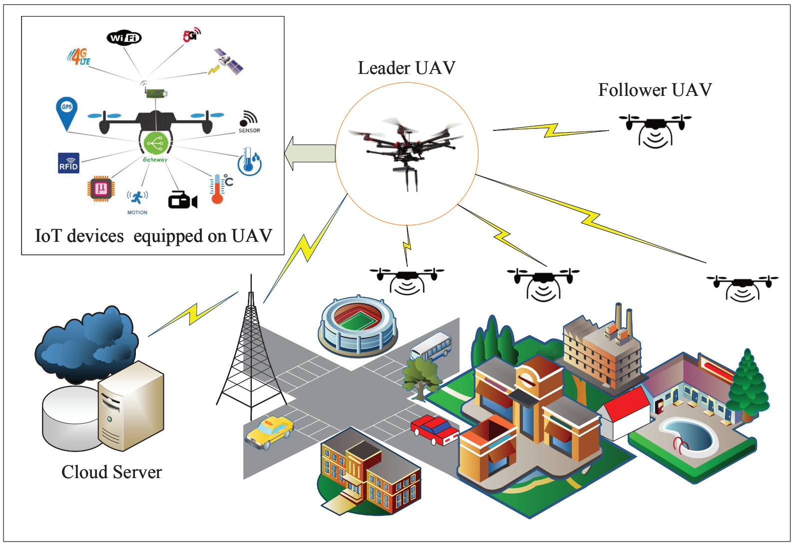

FIGURE 1. An example of UAV IoT.

Basics of SAG IoT

With the gradual popularization of aerospace and satellite technologies, the field of IoT has expanded from ground-based 2D architectures to land, sea, air and space multi-dimensional architectures. The UAV IoT was put into use first; then, based on the UAV IoT, a more integrated network, called the SAG (Space-Air-Ground) IoT, was proposed. The SAG IoT can work across a wide range of sea, air, international (cross-border) and remote areas, and it can provide information exchange between nodes at any time. The SAG IoT is the development trend of the future IoT.

UAV IoT

UAVs have attractive characteristics, such as being dynamic, easy to deploy and easy to control in flight. According to the forecast from the Prospective Industrial Research Institute [7], China's UAV market will reach 2.28 billion (US) dollars by 2022. Based on its numerous advantages, UAVs can support a variety of military and civilian services. Using remotely controllable IoTs or communication devices, many IoT applications can be created for UAVs [1], as shown in Fig. 1.

When equipped with a communication device such as WiFi, the UAV can serve as a temporary base station and a relay node. A broader application of UAVs is to collect IoT information; when equipped with IoT sensors such as cameras, a UAV-based IoT platform will be formed. Through this platform, IoT data can be collected via remotely controlled IoT sensors mounted on UAVs. Many tasks that require intensive use of manpower (e.g., oil field and high-tension line inspection, forest monitoring) may be completed more efficiently and successfully through this platform [7].

Two key technologies are vital to the proposed UAV-based IoT platform: the formation flight and motion control of the UAV groups, and the communications and IoT data processing of the UAV.

Multi-UAV formation flight can be divided into two categories: centralized control and decentralized coordinated control. In the centralized control method, the "Leader-Follower" model is a common method. In this model, the leader UAV is at the core and controls the flight of the entire forma-

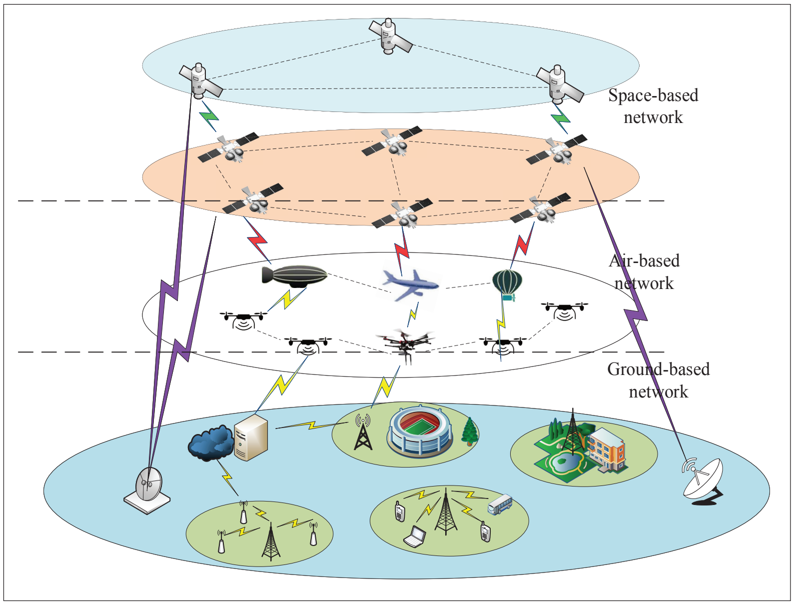

FIGURE 2. Structure of the SAG IoT.

tion. Each follower UAV travels along the path provided by the leader UAV. Under the decentralized collaborative control method, each UAV plans its own path independently and then sends its path to the other UAVs in the formation to prevent duplicate paths.

Regarding UAV communication, in the "Leader-Follower" model, the follower UAVs cannot communicate with each other or with the control station; they can only communicate with the leader UAV. The leader UAV acts as the fusion center and the network gateway, communicating with the ground control station and transferring the collected IoT data to this control station. Under the decentralized collaborative control method, UAVs can communicate with each other through wireless links. This configuration means that the failure of one node does not affect the operation of other nodes, which improves the reliability of the platform. Depending on the computing power of the UAV platform, the collected data can be processed locally or sent to the control station.

Regarding the future development of UAV IoTs, the most necessary breakthrough is a new battery or energy storage system that will improve the operation time. Increasing the onboard processing power will allow the UAV to offload the processing power from the server while reducing the required communication bandwidth. Integrating cloud computing and distributed processing into UAV IoTs can significantly improve the processing power of the platform. More and more autonomous flights will be allowed until it finally reaches the point at which the UAV does not operate as a device, but rather as a service that is fully integrated into a smart city machine-to-machine (M2M) network. In addition, the activities of UAVs usually have the characteristics of tendency and clustering when they carry IoT devices to perform specific tasks. Based on the individual mobility model (IMM), we can derive the UAV pause, arrival, and departure probabilities in a specific region. Such results are useful for improving the performance of the UAV network, predicting the trajectory of the UAV, and enhancing the control of the UAV system [8].

SAG IoT Network

The SAG IoT is the future of network development, because it can help deal with complex tasks in unpredictable environments. As shown in Fig. 2, the SAG IoT is a hybrid integrated network consisting of space, air and ground parts.

Space-Based Network: The space-based network is mainly composed of multi-layer satellite networks. The construction and implementation of the SAG IoT will require more than the single-layer satellite network, which is not suitable for the development of integrated networks characterized by diversification, backbone transmission and coverage globalization. In order to improve this problem, multi-layer satellite networks are combined. The advantages of different orbits will complement each other's shortcomings to meet the quality of service (QoS) requirements of different users. Multi-layer satellite networks use inter-layer and intra-satellite links to establish a reliable communication network that can achieve efficient real-time communication.

Air-Based Network: Air-based communication networks are an important part of the SAG IoT, as they can directly communicate with satellites and ground networks and make up for any shortcomings. In recent years, research on air-based networks has made great progress. The air-based network consists of low-altitude platforms (LAPs) and high-altitude platforms (HAPs). The diverse UAV IoTs mentioned before are the most typical applications of the LAP networks. HAPs consist mainly of large UAVs, airships or hot air balloons operating at high altitudes. HAP networks can provide wider coverage than LAP and terrestrial networks [7]. The biggest advantage of an air-based network is that it can be deployed quickly, and it can respond to temporal and distance traffic demands quickly.

Ground-Based Network: In a ground-based communication network, the terrestrial nodes (ground 5G base stations, relay stations, vessels and other mobile nodes) can be interconnected by point-to-multipoint (PMP) networks or mesh networks, thereby achieving various services. The ground nodes and the lift platform are connected by PMP networks to construct a ground-to-air remote broadband wireless relay communication network. Further, multiple lift platforms are interconnected by mesh networks to form a coverage network over a larger area.

The SAG IoT is a complex integrated heterogeneous network. Managing this complex system requires studying its network architecture. The software defined network (SDN) and network functions virtualization (NFV) help to realize globally optimized unified management and support the dynamic configuration of the devices in heterogeneous environments, allowing for flexible and efficient resource allocation on demand. SDN separates the control plane from the data plane, and introduces a unified data exchange standard and programming interface, which can realize the unified management of all devices in heterogeneous networks and support the global allocation of network resources. NFV refers to hardware and software that are decoupled by using common computing, storage, network hardware platforms and virtualization technologies. NFV is implemented in software, improving the

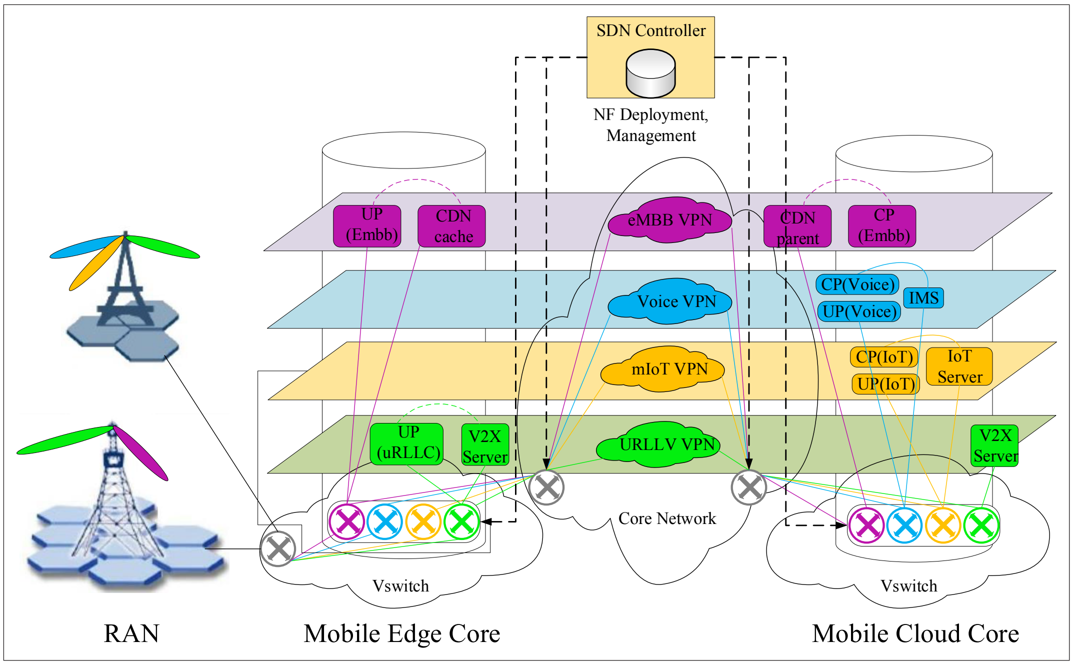

FIGURE 3. End-to-end network slicing in 5G.

The SAG IoT is an integrated network system that coordinates among space, air and ground networks. It greatly expands the coverage of a communications network and helps to collect, manage and coordinate multi-dimensional information. SDN and NFV are used to achieve dynamic allocation and management of resources, while the localized computing and storage functions provided by MEC can be used for fast service.

flexibility and reliability of systems [9]. In addition, many delay-sensitive services will appear in future IoT, such as autonomous driving. Mobile edge computing (MEC) technology was introduced to serve low-latency communications. MEC involves cooperation with cloud computing centers, allowing quick service for the applications of mobile terminals with the help of the computing and storage resources located at the edge of the mobile network. In addition, MEC can make full use of information about locations, channel states and terminal capabilities provided by the networks; this information is used to support location-based services, localization services, nearby fast calculations and other services that dynamically adapt to wireless conditions.

In conclusion, the SAG IoT is an integrated network system that coordinates among space, air and ground networks. It greatly expands the coverage of a communications network and helps to collect, manage and coordinate multi-dimensional information. SDN and NFV are used to achieve dynamic allocation and management of resources, while the localized computing and storage functions provided by MEC can be used for fast service. Combining these technologies, the SAG IoT can provide users with a diverse set of high performance and low latency new services.

Key Technologies of the SAG IoT

The SAG IoT is a new network model that offers many new services; however, certain key new technologies still need to be introduced.

Network Slicing

3GPP [10] gives the definition of network slicing: "A logical network that provides specific network capabilities and network characteristics." Through NS, multiple logical sub-networks with different characteristics can be deployed simultaneously on the same physical network, and the different requirements of the vertical industries could be met. NS includes slicing the core network and the radio access network (RAN), as shown in Fig. 3.

In the core network, SDN plays an important role. SDN controllers perform the provisioning of routers in the core network to create SDN tunnels (i.e., Virtual Private Networks (VPNs)) for different network services according to their specific requirements, and they manage VNFs in the clouds. For each network slice, isolation and dedicated resources such as resources within virtualized servers, network bandwidth and QoS are guaranteed. The MEC and mobile cloud core (MCC) connect to the core network. The user plane functions, the cache, and the V2X server can be placed in the MEC to accommodate the requirements of Ultra Reliable Low Latency Communications (uRLLC) and reduce traffic load in the core network.

The RAN side defines slices from the perspective of physical resources. Spectrum-level slicing is realized by techniques such as beamforming, time, space, frequency multiplexing, and overlapping access, which realizes the logical segmentation and on-demand dynamic allocation of air interface resources, breaking through the existing pattern of the fixed allocation of spectrum resources. The slice-selecting function is used to match the RAN slice and the core network slice to form the E2E connection.

Network slicing can be classified as static and dynamic slicing. In static slicing, network resources are exclusively preserved for each slice and do not change within a communication lifecycle, while in dynamic slicing, network resources are allocated according to the actual business demand. In dynamic slicing, we use a deep learning algorithm to analyze users' current and past traffic usage, and we then predict users' future traffic demand. Ultimately, the resources needed by the user at the next moment will be pre-allocated. In this way, the network resources can be allocated flexibly.

However, due to the characteristics of the SAG IoT itself, some difficulties remain in slicing the SAG IoT network. First, the spatial scale of the network is large with frequent link switching, and the network topology changes dynamically, so it is diffi-

Studying the propagation characteristics of wireless channels is the first step in constructing wireless communication systems. Only after fully studying and understanding the channel characteristics of the designed system, the various physical layer technologies can be adopted to optimize the performance of the system.

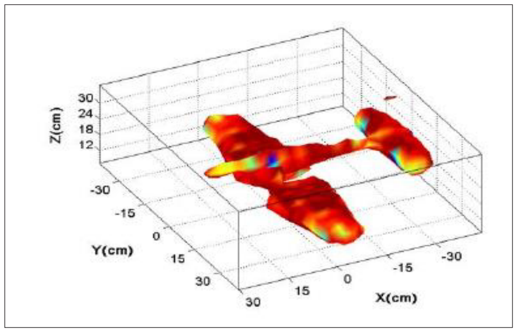

FIGURE 4. An example of mmWave 3D imaging of the UAV.

cult to effectively control the network. Second, the communication mechanisms and network protocols from the space, air and ground planes fail to form a unified standard. Third, the satellite network often experiences long delays and significant path loss; such transmission delays amplify the impact of network congestion and hinder the ability of the control layer to perform timely scheduling and coordination of communication resources. Furthermore, the motion of satellites and UAVs causes Doppler shifts in the signal. To solve these problems, further research is required, mainly including the management of the mobile node, the collaborative control and management of network devices, and the interconnection and interoperability of heterogeneous networks.

mmWave Channel Modeling for UAV Networks

Studying the propagation characteristics of wireless channels is the first step in constructing wireless communication systems. Only after fully studying and understanding the channel characteristics of the designed system, the various physical layer technologies can be adopted to optimize the performance of the system. The propagation mechanism of wireless signals could be divided into direct, reflection, scattering and diffraction. The signal will fade during the propagation process. The fading model is divided into the large-scale model and the small-scale model. The large-scale fading model reflects the variation of the received signal strength over distance, while the small-scale fading model reflects the multipath effect caused by environmental scattering. Channel modeling refers to the use of measurement data to obtain valid information about the channel (such as large-scale and small-scale parameters) to obtain an accurate and reliable mathematical model of signal propagation. Channel modeling provides an important reference for communication system design and technology standardization.

The mmWave band is a key component in 5G. As compared with the traditional frequency band, the mmWave band has many new propagation characteristics, meaning that any path loss in the mmWave will be more serious than the traditional low frequency signal. And, in the SAG IoT, there will be many new application scenarios. Due to the differences in frequency bands and scenarios, the existing channel models cannot describe the propagation characteristics of the SAG IoT channel.

UAVs will be widely used in the SAG IoT. Flying UAVs will have an important impact on signal propagation. The existing channel model cannot describe the impact of UAVs on signal propagation, and there is also no research on related content in the current literature. Therefore, in this article, we give an example of how to model the channel with a propagation path that passes through the UAV.

The influence of UAVs on signals can be divided into two aspects, including:

- When the signal encounters a UAV during the propagation process, due to the reflection, scattering and diffraction of the UAV, multiple propagation paths will be generated, which is called the multipath phenomenon. The received signal is a superposition of the multipath signals, and mutual interference between the multipath signals will cause small-scale fading of the received signal.
- The motion and micro-motion of the UAV will modulate the frequency of the wireless signal, causing the frequency of the signal to shift.

In order to model the channel with a propagation path that passes through the UAV, the first thing we need to do is to study the reflection, scattering and diffraction effects of UAVs on mmWave signals. This related information can be obtained by performing mmWave 3D imaging of the UAV. Then, we need to analyze the frequency modulation effect of the UAV on the mmWave signal. On the basis of the above research, we then select an appropriate channel modeling method, and the mmWave channel model for UAV networks will thus be obtained.

mmWave Measurement of UAV: The UAV can be seen as being composed of many scattered points. When the mmWave signal propagates to the UAV, complex reflection, scattering and diffraction will occur, and a cluster of multipath signals with similar delays and angles of arrival (AoA) will be generated. The characteristics of the multipath signal (e.g., delay, azimuth, AoA) are determined by the distribution of the scattering points of the UAV. By performing mmWave 3D imaging of the UAV, the distribution and composition of the scattering points of the UAV can be obtained, and the more geometric features of the UAV, such as the lateral length and the area size, can be extracted.

The basic principle of mmWave 3D imaging is as follows. We use a mmWave transmitter to emit a mmWave signal. When the transmitted signal reaches the target, reflection, scattering and diffraction will occur. Then, the multipath signal that was generated will be received by the receiving system. By performing Fourier Transformation on the received signal, a single strong scattering point becomes an impulse function in the 3D space. If the target has many strong scattering points, the imaging result will be the sum of the multiple points. An example of mmWave 3D imaging of the UAV is shown in Fig. 4.

In this section, we have provided a new idea: identifying the distribution of strong scattering points of the UAV by performing 3D mmWave imaging. This is an innovation first proposed in this article. Next, according to the imaging results, the reflection, scattering and diffraction effects of the UAV on the wireless signal can be further analyzed, which is crucial for channel modeling.

Signal Doppler Shift Analysis: The motion of the target causes a Doppler shift in the received signal. The Doppler shift reflects the time-varying characteristics of the channel, which can seriously impact the communications, especially for OFDM systems. When a Doppler shift occurs, the orthogonality among the sub-carriers of the OFDM system is to be affected, and the accuracy of channel estimation is to be degraded too. These affects will increase the bit error rate (BER) at the receiving end and decrease the performance of the communication system. Thus, it is necessary to study the Doppler shift and its influencing factors to reduce its impact on the performance of the receiving system. While in the SAG IoT scenario, many UAVs will be used, and the Doppler effect caused by the motion of the UAVs cannot be ignored. However, very few papers have discussed this topic so far.

To analyze the Doppler effect produced by the UAVs, we first need to study the motion of the UAV. The motion of the UAV is complicated; specifically, it can be divided into translational and micro-motion. The translation is caused by the change of the position of the object, which is well understood. Next, we introduce the micro-motion. Micro-motion refers to small movements of the target or its components, such as vibration, precession and rotation caused by something other than the translation of the centroid. When the target is in the micro-motion state, an additional frequency shift in addition to the Doppler shift caused by the translation is generated in the signal, which causes the Doppler spectrum to broaden. This effect is called the "micro-Doppler effect" [11]. For UAVs, the rotation of the propeller triggers the micro-Doppler effect, and studies have shown that the higher the carrier frequency, the more obvious the micro-Doppler effect. Up to now, all applications subject to the micro-Doppler effect have been limited to the detection of target characteristics in radar systems. The frequency shift of the wireless signal caused by the Doppler effect has been neglected.

The micro-Doppler shift caused by micro-motion is a time-varying frequency function. Experiments show that the frequency shifts generated by the target with and without micro-motion are categorically different. Frequent time-frequency analysis is often used to analyze micro-Doppler shifts, which can simultaneously analyze signals from both the time and frequency domains. By taking the time derivative of the phase, the Doppler frequency shift induced by the target's motion can be obtained; specifically, it is the sinusoidal curve, and it will modulate the carrier frequency in the manner of periodic time variance.

The multipath signal Doppler propagation model is proposed in [12]. In this model, the frequency of the received signal consists of three components: the carrier frequency, the Doppler shift and the micro-Doppler shift.

In this section, we studied the Doppler shift of the signal caused by the motion of the UAV. The next step is to explore some ways (such as adaptive transmission based on the current Doppler shift) to circumvent related issues and improve system performance.

3D mmWave Channel Modeling for UAV Networks: Based on the above two studies, we will model the channel for UAV networks. According to the modeling approach, channel models can be classified into stochastic channel models and deterministic channel models. Generally speaking, stochastic models describe channel parameters using certain probability distributions. They are mathematically tractable and can be adapted to various scenarios, but with relatively low accuracy. Deterministic channel models predict the propagation waves in a more accurate manner by solving the Maxwell equations, which requires more complicated calculations [13].

In past studies, the modeling of the channel was generally based on the assumption that the scatters were distributed on a 2D plane, regardless of the elevation plane. As the frequency band increases, the propagation characteristics of the signal will change. The assumption of 2D propagation may lead to an inaccurate estimation of the channel parameters. Therefore, it is necessary to establish a 3D propagation model of the mmWave signal and study the propagation characteristics of the signal in the space, time and frequency domains under different scenarios.

The 3D ray tracking method relies on the real physical environment to treat electromagnetic waves as rays, simulating the principle of light propagation and obtaining the characteristic parameters of radio wave propagation. 3D ray tracking can predict the reflection, scattering and diffraction of dominant channel components with limited computation times even in complex environments. It is recognized as a reliable tool to simulate accurate mmWave channel properties, and it is often used to complement time consuming and expensive measurement processes [14].

When using ray tracing for channel modeling, geometric modeling of the scenes provides the basis, and the accuracy of the 3D scenario models will affect the accuracy of the results. Considering the impact of UAVs on signals, we import the 3D mmWave image of the UAV, the Doppler shift and the micro-Doppler affect caused by the UAV into the simulation system to simulate the UAV in the real environment. The second step is to set the simulation parameters (e.g., transmit power, antenna height, number of UAVs, angle of departure (AoD)). The third step is to simulate the propagation of wireless signals based on ray tracing. Finally, the parameters of each path of the multipath signal (e.g., angle of arrival (AoA), time of arrival (ToA), phase, amplitude) will be obtained. Statistical information about multipath signals (e.g., the power delay profile (PDP), power angle spectrum (PAS), power spectrum density (PSD), root-mean-square (RMS) delay) can be obtained at the receiving end.

Through the mathematical analysis and statistics of the data obtained by the ray tracing method, the 3D multipath channel model and related channel coefficients under the UAV IoT could be derived. Finally, the genetic algorithms can be used to correct channel parameters to further reduce modeling errors.

An Integrated 5G Measurement and Simulation Platform

Network simulation plays an irreplaceable role in communications research. In the process of network design, simulation software can simulate network protocols, hardware resources and specific network connections from the link, system and network levels to obtain network parameters. Through simulation, system performance can be predicted, problems can be found in a timely fashion, and workload can be reduced.

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To speed up the simulation, the GPU is used, and the calculation task is assigned to the cloud-computing node by means of the central node. The simulation results are stored in the cloud, and the user can download them when necessary. With this design, the proposed simulation platform has the advantages of scalability, flexible resource calling and self-management.

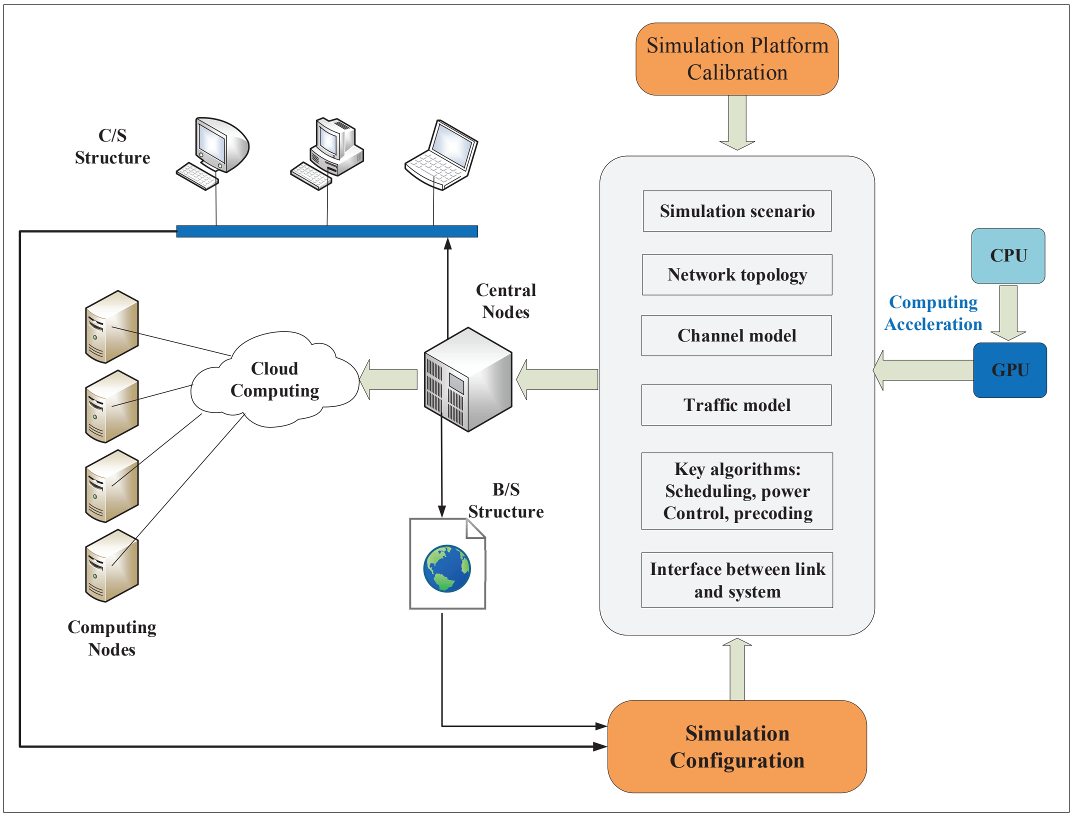

FIGURE 5. Framework of the proposed simulation platform.

Measurement is also vital. First, the new channel model is based on data obtained from channel measurements. Second, measuring the physical layer data and analyzing the characteristics of the data is helpful for selecting the appropriate simulation algorithm. Third, the real performance of the system must be obtained by measurement.

With the development of the SAG IoT and 5G, innovations in simulation and measurement are needed to meet new requirements.

New Simulation System

Compared with fourth generation (4G), 5G and the SAG IoT system are more difficult to simulate. The interconnection and integration of multi-dimensional networks have changed the traditional network architecture. Also, the application of new technologies such as SDN, NFV and MEC make it more difficult to predict the network's behavior. Likewise, the emergence of innovative applications and new evaluation indicators require us to obtain more accurate parameters for the wired and wireless networks.

The 4G simulation platform cannot be applied to the simulation of 5G and SAG IoT. Therefore, a new simulation platform must be developed for the SAG IoT. To adapt to the various application scenarios that may occur with the SAG IoT, the new simulation system must be modular and scalable. Also, more precise propagation models and more input parameters are essential. Network resource management and scheduling algorithms that match the core technologies such as SDN, NFV and machine learning-based traffic prediction algorithms should be introduced. The changes in network topology and Doppler shifts in the signal caused by the motion of satellites and UAVs should also be considered. Furthermore, due to the more complicated configuration of simulation parameters and the huge amount of user interaction information, the need for data storage is greater, making simulation efficiency a bottleneck in new simulation systems. We have three options to speed up the simulations: multi-machine and multi-core parallel simulation, hardware acceleration, and cloud computing. A new system level simulation platform that meets the above requirements is proposed in [15], as shown in Fig. 5.

As we can see from the above figure, the new simulation system integrates various inputs to achieve a more accurate performance evaluation. The main body of the simulation system is realized by the modularization, in which different modules are responsible for different functions, such as channel model and interference calculations. The parameters that are inputted are used to configure the corresponding modules, and different simulation conditions are achieved by changing the input of each module. The simulation platform is based on cloud computing and interconnected with the Internet. The configuration parameters can be entered via the web or via the input software. To speed up the simulation, the GPU is used, and the calculation task is assigned to the cloud-computing node by means of the central node. The simulation results are stored in the cloud, and the user can download them when necessary. With this design, the proposed simulation platform has the advantages of scalability, flexible resource calling and self-management.

Measurement

Measurement and simulation are equally important in the design of communication systems. In this section, we demonstrate this by taking the example of measuring the physical layer data. In the simulation process, we need to predict the traffic and data in the network slice. By understanding the basic characteristics of the network physical layer data, we can select an appropriate algorithm to predict the data. The features of 5G NR physical layer data mainly include system time, resource block ID, SNR and subcarrier.

Through measurement and analysis, it is found that the basic characteristics of the data have a strong correlation. For example, the traffic load at a certain moment has very similar trends with adjacent moment, which provides an important basis for the selection of the prediction algorithms. Traditional prediction techniques are mainly divided into time series model-based prediction methods and probability model-based prediction methods. The time series model-based prediction method can only predict linear correlation sequences, and the probabilistic model-based prediction method cannot predict the detailed features of the sequence accurately, therefore, neither of these types of methods produces satisfactory prediction results. Recurrent neural network (RNN) is a kind of artificial neural network with memory, because of its memory characteristics, RNN meets the requirements for predicting physical layer data. Therefore, in the simulation platform, RNN will be used to forecast the feature of 'power' in the physical layer data. Long short-term memory (LSTM) is a variant of RNN; LSTM solves the problem of the vanishing gradient in RNN. In the simulation process, LSTM will be used to forecast the 'SNR' characteristic of the physical layer data. Gated recurrent units (GRUs) is another variant of RNN, and it solves the overly complex computing problems of RNN. GRUs will be used to forecast the 'frequency' characteristic of the physical layer data.

After introducing the network architecture and key technologies of the novel SAG IoT, we compare the proposed method with the existing methods. First, the existing network architecture is relatively simple, it is usually limited to space-ground or air-ground networks, and these networks only provide single-type services such as voice communication. The SAG IoT system, on the other hand, fundamentally integrates the space-based, air-based and ground-based networks and provides a full range of services, including IoT service. Second, the novel SAG IoT uses the latest technologies, such as SDN, NFV, MEC and AI, while existing methods rarely use these new technologies. Third, in the SAG IoT, the RF impact of UAV on communication is taken into consideration, and the SAG IoT includes channel models and application scenarios that the existing methods do not. Fourth, compared with the existing simulation system, the newly proposed distributed modular simulation system has higher computational accuracy and efficiency.

Simulation

Since the SAG IoT is a complex system, much research on related aspects is not yet matured. Thus, in this section, we simulate only the communication under the UAV network scenario to verify the impact of UAVs on communications.

The simulation scenario is a typical 5G cell, the measured 3D mmWave images of the UAV at various angles are imported to the simulation platform, and the UAVs use the "Leader-Follower" model for formation flight. We set the carrier frequency to 28 GHz, the transmitting power of the antenna is 30 dBm, and we use the new channel model. The Doppler effect caused by the motion of the UAV is also taken into account, and we then observe the change in the performance of the receiver by changing the number of UAVs deployed in the cell. We analyze the power, multipath angular expansion and multipath delay of the receiver under different UAV densities. The simulation results are shown in Fig. 6.

In Fig. 6a, we can see that the signal power at the receiving end decreases as the density of UAVs in the cell increases. This phenomenon can be explained by Fig. 6b. In Fig. 6b, we show the power spectrum of the received signal when the number of UAVs in the cell is 3, 10 and 30, respectively. It can be intuitively seen that when the deployment density of the UAVs is very low, the energy of the signal is concentrated in the carrier frequency band, and the energy loss is small when the signal passes through the band pass filter at the receiving end. When the UAVs are deployed at a high density, due to the Doppler effect and the micro-Doppler effect caused by the UAVs, the peak value of the received signal's power spectrum will decrease, and the frequency will broaden, resulting in a large energy loss when the signal passes through the filter. Fig. 6c shows that as the density of the UAVs increases, the angular spread of the signal at the receiving end will become larger. Similarly, Fig. 6d shows that as the density of the UAVs increases, the delay in receiving signals will grow. This occurs because as the number of UAVs increases, the reflection, scattering and diffraction effects of the UAVs on the signal become stronger, making the multipath phenomenon more conspicuous and resulting in an angular spread of the signal and an increase in system delay. In summary, the simulation results have validated the models.

Conclusion

This article proposes a novel SAG IoT network paradigm based on the Space-Air-Ground heterogeneous architecture. In our design, the UAV plays a pivotal role by adopting network slicing and mmWave channel modelling. Since the flying UAV can easily reflect 5G signals, we pay special attention to the impact of UAV on wireless signal propagation under different RF environments. We first utilize UAV mmWave imaging to investigate the reflection, scattering and diffraction characteristics of UAV in mmWave bands, and then further take into account the Doppler and micro-Doppler effects caused by the motions and micro-motions. Finally, we conduct an integrated measurement and simulation study for a multi-perspective performance evaluation.

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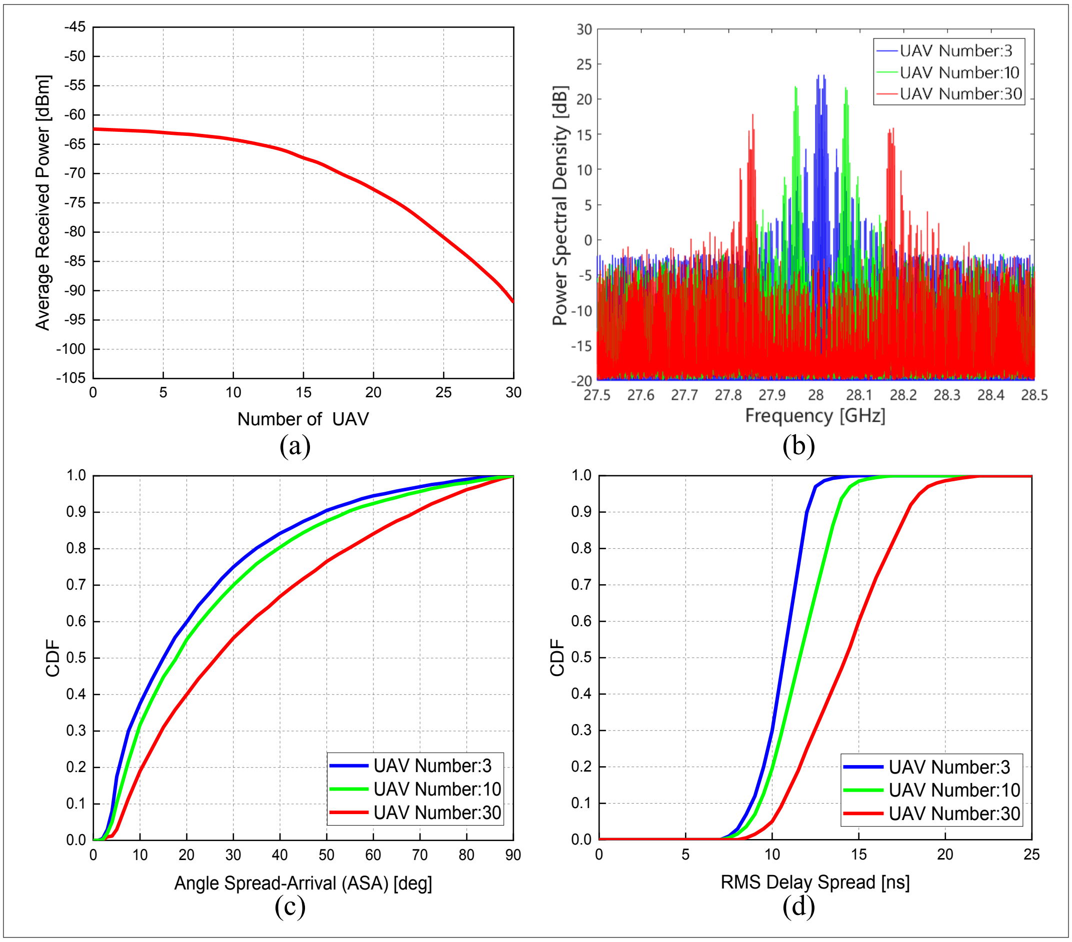

FIGURE 6. Performance evaluation results for different UAV deployment densities: a) average power at the receiving end vs. the number of UAVs deployed; b) the power spectrum of the received signal under different UAV deployments; c) the ASA of the received signal under different UAV deployments; d) the RMS delay spread of the received signal under different UAV deployments.

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